Human-activity-centered measurement system: challenges from laboratory to the real environment in assistive gait wearable robotics

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Human-activity-centered Measurement System: Challenges from Laboratory to The Real Environment in Assistive Gait Wearable Robotics

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Abstract: Assistive gait wearable robots (AGWR) have shown a great advancement in developing intelligent devices to assist human in their activities of daily living (ADLs). The rapid technological advancement in sensory technology, actuators, materials and computational intelligence has sped up this development process towards more practical and smart AGWR. However, most assistive gait wearable robots are still confined to be controlled, assessed indoor and within laboratory environments, limiting any potential to provide a real assistance and rehabilitation required to humans in the real environments. The gait assessment parameters play an important role not only in evaluating the patient progress and assistive device performance but also in controlling smart self-adaptable AGWR in real-time. The self-adaptable wearable robots must interactively conform to the changing environments and between users to provide optimal functionality and comfort. This paper discusses the performance parameters, such as comfortability, safety, adaptability, and energy consumption, which are required for the development of an intelligent AGWR for outdoor environments. The challenges to measuring the parameters using current systems for data collection and analysis using vision capture and wearable sensors are presented and discussed.

Keywords: wearable devices, human-centered robots, gait analysis, assistive robotics, computational intelligence

1. INTRODUCTION

Assistive robots encompass a wide area of research in which the researchers deal with the design of the devices to assist, rehabilitate [1] or replace the limb that has been no longer in function. The gait parameters are essential in design and performance evaluation of such devices used by unilateral transfemoral amputees or those who suffer from lower limb disability. It is a common practice to use motion capture (Mo-Cap) system to trace and record the movement of the human limbs throughout a certain activity to evaluate the human gait performance. There are currently a number of different type of systems available to capture such activity including, photogrammetry (video-based system) [2], [3], wearable sensors [4], [5], and inertial measurement units (IMUs) [6], [7]. Video-based motion capture devices have been commonly utilised to evaluate the functionality and performance of the assistive devices in the laboratory environment [8], [9], which require major preparation and patient briefing before starting to gather data. In addition, the devices require large laboratory spaces and are expensive hampering the use in many universities with a low budget. On the other hand, with the advancement of sensory technologies and the analysis methods, gait analysis using wearable sensors is expected to play an increasingly important role in design, performance evaluation and control of assistive robots in the future [10]. This paper focuses on the gait parameters that were identified in a research project (Smart BioLeg) funded by the Engineering and Physical Sciences Research Council (EPSRC) to address key shortcomings of the prosthetic knees currently available on the market and hence provide the enhanced levels of flexibility, adaptability, actuation, and robustness that unilateral transfemoral amputees of the lower limb require to carry out activities of daily living. The parameters along with the measuring devices provide a portrait of the gait performance parameters that are directly affecting assistive robotics devices, users comfort and functionality.

2. THE ROLE OF GAIT PARAMETERS IN THE DESIGN, CONTROL AND PERFORMANCE EVALUATION OF ASSISTIVE GAIT ROBOTS

Gait analysis is a systematic study of human locomotion, which is defined as body movements through aerial, aquatic or terrestrial space [11]. This analysis involves the

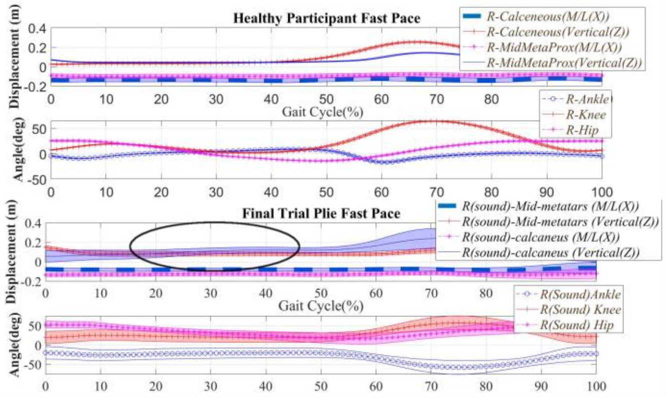

Fig. 1. Vaulting of a transfemoral amputee is shown in comparison to the non-amputated participants. The intact ankle must flex and rise to produce the needed clearance for the amputated side (Black ellipse shows the rise of the passive calcaneus marker from the ground on the intact side of a transfemoral amputee).

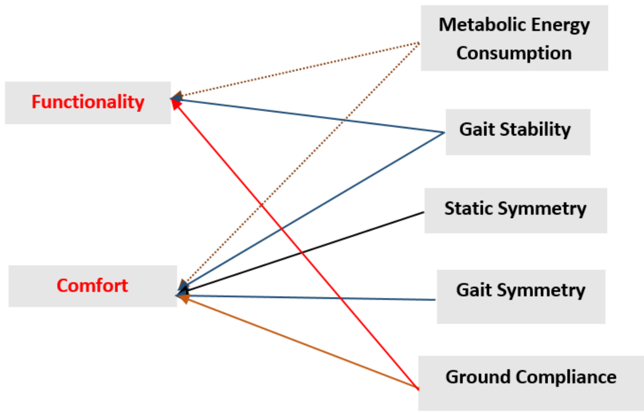

Fig. 2. Relating functionality and comfort of a prosthetic knee to gait parameters of amputees.

registration and reconstruction of physical location and orientation of individual limbs used to quantify and characterize human locomotion using different gait parameters including the gait phases, spatiotemporal and kinetic parameters of human gait [12]. To measure gait parameters in the photogrammetry system, a minimum of two fixed cameras along with a force platform and reflective markers attached to the anatomical landmarks, are required to estimate gait parameters. This method is limited to be used inside the laboratory space and it is expensive, although it is considered fairly accurate when compared to sensory based measurements [13]. The onboard embedded and wearable sensors have been widely used to detect the gait analysis parameters; such as stride length, stability, gait events and phases, segment angles in the indoor and outdoor environment. Wearable sensors are low-cost, convenient and efficient sensors for providing useful information of gait, user intent and AGWR state for controlling and assessing the amputee-prosthesis interaction [14]. For the design of a prosthetic knee, it is important to obtain the maximal and minimal dynamic forces at the joint associated with a range of individual activities. However, it is difficult to directly measure the segmental forces/torques in the knee joint as it requires some invasive methods to be utilised. Estimating dynamic loads are far more difficult to predict in AGWR compared to static loads that are estimated at certain posture, and this is especially true in systems with multiple moving parts, e.g. hydraulic systems [15]. To overcome the challenges involved with invasive measurements, a combination of Mo-Cap and multi-body simulation [16], [17] is commonly used to estimate the joint maximal and minimal forces and moments for the design of any assistive robots including implants. A key feature of the human gait is its ability to conform well to changing terrains and walking paths. In unilateral lower extremity amputees with larger amputation the ability of adaptation decreases. An example is transfemoral amputees who have a higher prevalence of circumduction and/or vaulting [18] (Figure 1) than transtibial amputees. As it is shown in Figure 1 such gait abnormality can be identified using video-based Mo-Cap system vertical displacement of the amputees leading leg.

Despite large advancement in design of prosthesis, a study by Gotthard and Stills [19] and a survey by Sapp and Little [20] have shown that the comfort (52%) and functionality (38%) have still been ranked among the highest requirements by the amputees users and over 50% of amputees tend to wear their prosthetic leg for less than an hour per day. It has been quite a difficult task to identify what parameters affect both functionality and comfort of a lower limb prosthesis and how to evaluate them to improve the overall amputee mobility. However, one of the objectives of the Smart Bioleg project was to identify the parameters affecting both functionality and comfort in the lower limb amputees to find the inter and intra-relationships of the factors along with measuring parameters and the devices which enable us to objectively quantify them. Figure 2 shows the relationship between gait performance parameters and two important outcome factors for any AGWR [19], [20]. The following section describes the performance indices and parameters shown in Figure 2.

3. MEASURING PERFORMANCE INDICES FOR GAIT EVALUATION AND CHALLENGES

Two major methods of collecting gait performance data, using vision based motion capture and wearable sensors, are described in this section.

3.1 Vision-based motion capture (photogrammetry)

In the photogrammetry approach infrared optical cameras are used as a vision system, and fiducial is placed on the participant’s anatomical site in form of passive or active markers. These are used to measure the kinematics and spatiotemporal parameters of human gait, while force platforms are used for directly measuring ground reaction forces to estimate the gait dynamic parameters. However, this approach is very expensive, time consuming and limited to be used inside the laboratory spaces and is not quite suitable for outdoor activities. At the University of Leeds, a Qualisys Motion capture system (Qualisys AB, Sweden) was used, which comprises 12 Qualisys Oqus 4 cameras and 1 Qualisys Oqus 310 high speed video camera. The camera system was configured to collect data at 400 Frame per second (fps) through QTM software. In addition, AMTI force platforms embedded to the ground (Watertown, MA, USA) were used to measure gait events and ground reaction forces (GRFs). The force plate data was set to 1200 samples per second. Another portable force platform was used to collect GRFs during ramp and stair activities. The preparation time for every activity starts with calibration of the required area, placing reflective markers on the anatomical sites to establish the location of the joint centres and define limb segments tracing the location and their orientation in the three-dimensional laboratory environment. The results of the three-dimensional gait and motion analysis are highly dependent on the placement of these markers, which is one of the major sources of error in kinematic data [8], [9], [21], [22]. Figure 3 shows an above-knee (AK) amputee performing some activities of daily living in the laboratory environment.

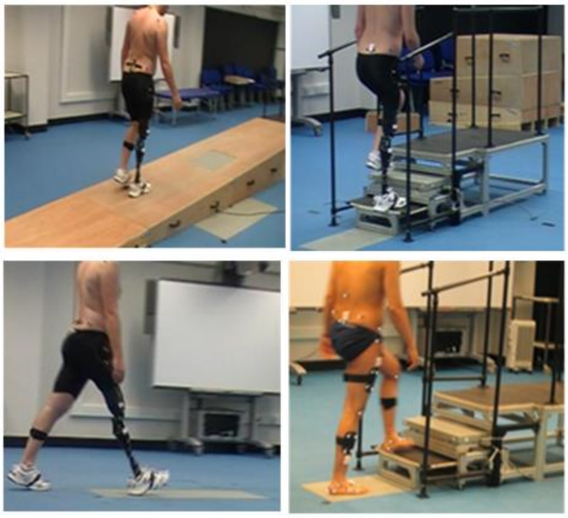

Fig. 3. IMU data collection during activities of daily living for AK amputee and healthy subject.

The quantitative assessment of the assistive gait wearable devices and technologies is crucial for their performance evaluation, improving performance and identifying their proper competitive market position, in addition to their potential use in the future smart devices. To evaluate the wearable devices such as exoskeletons, orthoses, and lower limb prostheses, different performance indices are used based on biomechanical and physiological parameters. These parameters are utilized directly or indirectly to evaluate the overall system functionality and the level of user comfort and reduced mental efforts due to the human-device interaction. The human-device interaction and functional outcomes of AGWR are mutually related and affect one another. The human-device interaction impacts the comfort of a user, it can be classified and indirectly estimated as follows:

Physical impact: results from the physical contact forces (normal and shear forces), between the wearer and the device, which are critical for the comfort. These parameters can be measured indoor using force platforms and gait analysis tools through an inverse dynamics calculation, in the outdoor setup, such measurement can be metered with force wearable sensors such as a force-sensing resistor (FSR) and flexiforce sensors.

Cognitive impact: results from the likely difference between the intention of movement and the actual movement of the wearable device. This requires more accurate intuitive control system based on activity recognition and machine learning approaches. The intention detection accuracy, reliability, and processing speed of this intuitive control should be considered as well for interaction performance index.

Physiological impact: is measured by estimating the heart rate, blood pressure, oxygen consumption and muscle activity to assess the effects on the user due to wearing AGWR.

Feelings and mental efforts impact: this is related to the feelings and mental efforts of the wearer when they use the device. Current approaches to assessing them are based on subjective methods using questionnaires filled in by users. We believe that impact can be objectively estimated using Electroencephalography (EEG) and/or Galvanic Skin Response (GSR) sensors or monitoring the facial expressions.

Safety impact: is related to the functional and biomechanical safety of the user and the device interaction while using it in different environments and terrains. The safety criteria should be carefully considered while designing any AGWR system. Although ISO 13482 standard sets the safety requirements and criteria of assistive robots, including wearable exoskeletons, it does not provide considerations for the measurement of biomechanical safety. The functional safety can be related to the user-device stability, maintaining postural balance or the device fail-safe criteria, while the biomechanical safety will be related to the forces transmitted to the wearer's joints and spinal which may create serious problems and damage. These biomechanical safety parameters can be estimated from the kinematics, kinetics and gait analysis tools used in the motion capture laboratory, which are limited to indoor use.

Among these five impact, the physical impact can be measured directly or indirectly using force and kinetics sensors while the cognitive, physiological, feelings and mental efforts, and safety impacts can be estimated based on a further computational analysis which affects their accuracy and possibility of using them in real-time. The physical impact is easier to be used in the real-time assessment, evaluation, and control. The future technologies may provide more accurate and fast estimation of cognitive, physiological, feelings and mental efforts, and Safety impacts which can affect the development of new generations of smart assistive rehabilitation devices and robotics. The overall performance of the wearable system functionality can be evaluated based on the following parameters:

Stability (static and dynamic balance): gait stability is often described as the ability to recover from perturbations, which arise during performing activities of daily living (ADL) from internal sources such as neuromuscular and external sources (e.g. wind, surface friction and/or uneven surfaces) [23]. This means that the individual postural stability depends on the neuro-musculoskeletal capacity and also on the type and magnitude of external perturbations encountered in ADLs.

Hence, the good balance and stable mobility involve continuous control and regulation of the human joints and muscles based on the central nervous system decision to determine the body's posture in relation to the environment and maintain the center of mass (CoM) within the stability projection polygon. The stability is classified into static and dynamic stability, which are needed for quiet standing and to maintain postural balance during any movement. There were some measures used to evaluate the stability such as maximum Lyapunov exponent of human gait, based on kinematic data obtained using motion capture systems or wearable sensors such as accelerometers. Center of pressure (CoP) and center of mass (CoM) are other measurements to be considered for stability evaluation. However, they can be measured using gait analysis laboratory based on the cameras and force platforms.

Energy Consumption: the energy consumption plays a significant role in evaluating the device performance. There are two types of energy associated with wearable assistive robotics. The first type is the metabolic energy consumption of the user when s/he interacts with the device. The second type of energy consumption is associated with the energy consumption and efficiency of the device. Efficient devices should consume less energy. In users, the metabolic energy consumption has been measured using VO2max testing, while the assistive device energy consumption has been measured using mechanical and electrical power formulation and physical measurement sensors.

Rollover shape: the knee-ankle-foot (KAF) roll-over shape (ROS) is a scientific method which has been used to compare performance and design of the different prosthetic foot types. In Smart BioLeg project, the influence of the prosthetic components (i.e. knee and foot) on the knee-ankle-foot roll-over shape in a unilateral transfemoral amputee was evaluated (Figure 4). The kinematics of the center of pressure (CoP), lateral knee, and ankle markers path were collected and processed to obtain ROS. The results were used to fit a circular shape arc to obtain the radius of curvature (ROC). This rollover shape is measured using gait analysis and motion capture systems in the laboratory and it cannot currently be measured using wearable sensors.

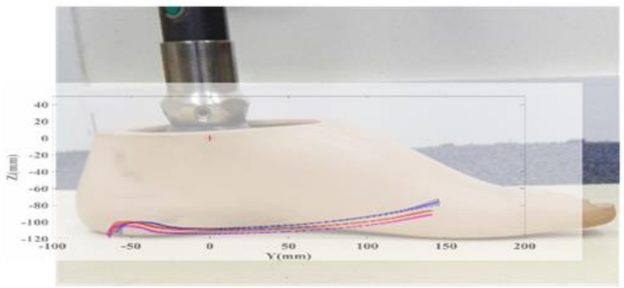

Fig. 4. A typical rollover shape of amputee with Rheo3 knee and Venture College Park prosthetic foot.

Static symmetry: static symmetry refers to the symmetry in weight-bearing load between left and right legs. This symmetry represents the user confidence while using the assistive device, which highly depends on the device design, functionality and user her/himself. This can be measured using wearable force sensors inside the insole of any AGWRs.

Gait symmetry: gait symmetry is one of the assessment criteria used to evaluate the performance of the wearable assistive devices and robotics. It refers to the percentage of the similarity between the left and right legs. It is defined as a performance index of abnormal walking and used for clinical assessment [24], [25]. Gait asymmetry or symmetry index (S_I) was calculated based on the following equation [26]:

$$S_I = \frac{X_R - X_L}{0.5 * (X_R + X_L)} * 100\% \quad (1)$$

Where X_R and X_L are the metrics for right and left limbs. The gait asymmetry can be evaluated using either spatiotemporal such as stride length, stance time ratio, step time, gait events or kinematics such as angles and velocity and/or kinetics parameters such as joint forces and ground reaction forces (GRFs) of the gait. This can be measured using both motion capture systems or wearable sensors [27].

Ground compliance (adaptability to the environment): adaptability to different terrains and environments is one of the challenges which needs to be presented to the AGWR functionalities, design and control. Human has great ability to adapt to different terrains by kinematically redundant joints across the lower extremity. The AGWR should be smart enough to be able to adapt and comply with different terrains and environment as an ordinary and healthy human does. This adaptability depends on the reaction of the mechanical system design and the control systems to the change in the environments. This can be measured indirectly using wearable sensors or using motion capture system by monitoring the change in kinematics, kinetics of the device and the user compensation. Figure 5 summarises the suggested assessment parameters in this section for both, the device functionality and the interaction comfort level.

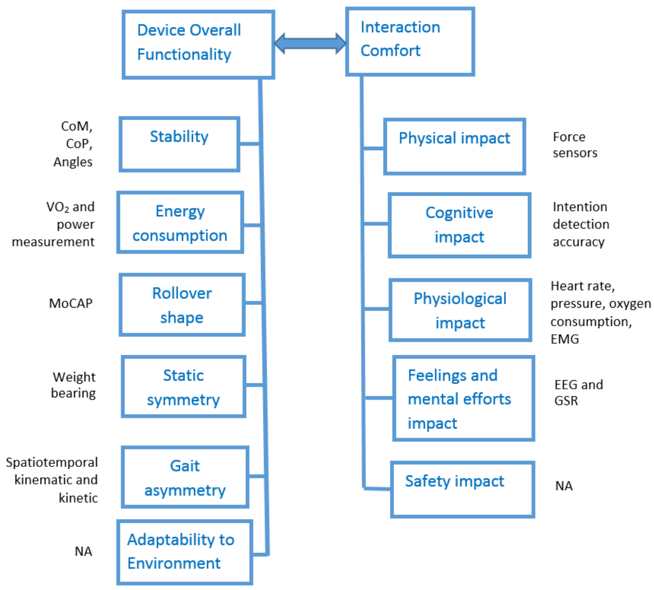

Fig. 5. The parameters used for assessment of the wearable gait robotic systems functionality and comfort level.

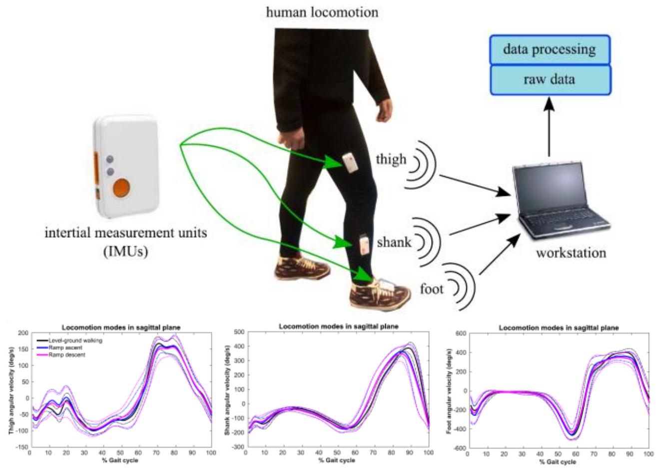

Fig. 6. (A) IMU sensors attached to lower limbs for collection of angular velocity signals while walking. (B) Example data collected from level-ground walking, ramps ascent/descent.

Challenges in collecting video motion capture system: there were several challenges in collecting the video motion capture data, which must be kept in mind when such a process is considered. The setup of the video-based motion capture is itself a lengthy process as calibration of the environment is necessary before starting. The process of placing the reflective markers on anatomical landmarks is another challenging aspect and requires palpating the proper location of the participant's body. Another challenging aspect of this form of recording is the interference of light or the participant's body parts, the reflective markers may be blocked causing data loss.

3.2 Wearable sensors

Wearable sensors are becoming very popular in assistive and rehabilitation robotics given their lightweight, small size, and low energy consumption. Commonly, these sensors provide data from angular velocity, acceleration and muscle activity, e.g., contraction and relaxation. The next generation of exoskeletons, composed of soft and lightweight materials, integrate wearable inertial measurement units (IMUs) and surface electromyography (sEMG) sensors for measuring kinematic data during activities of daily living (ADLs). Normally, these data are employed for recognition and control for the assistance of humans in their ADLs.

1) Wearable sensors for walking activities: An example of IMU sensors were used for data collection and recognition of locomotion activities is shown in Figure 6(A). Three IMUs, attached to the lower limbs of a subject were used to collect angular velocity data from level-ground walking, ramp ascent, and ramp descent activities. Examples of the data collected are shown in Figure 6(B). These data, together with machine learning methods, were employed for recognition of walking activities, gait phases, and events in a laboratory environment.

A Bayesian approach, implemented in MATLAB, was employed for recognition of walking activities [7], [28]. As it is shown in Figure 7, This approach provided high accuracy recognition results. It is believed that the high accuracy recognition results were obtained because of experiments being performed in a controlled laboratory environment.

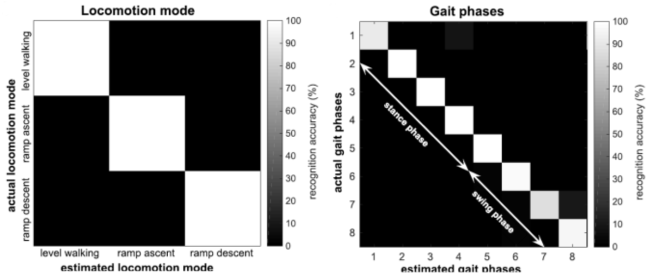

Fig. 7. (A) Recognition accuracy of locomotion activities. (B) Recognition accuracy of gait phases and events.

2) Wearable sensor for sit-to-stand activity: An experiment for recognition of sit-to-stand (SiSt) and stand-to-sit (StSi) activities, was also performed in a laboratory environment using one IMU sensor attached to the thigh of the participant (Figure 8(A)). For this experiment, participants were asked to perform multiple repetitions of SiSt activity to collect acceleration data from one IMU. Examples of the data collected are shown in Figure 8(B). The raw data are noisy and a pre-processing step was included to obtain smooth signals.

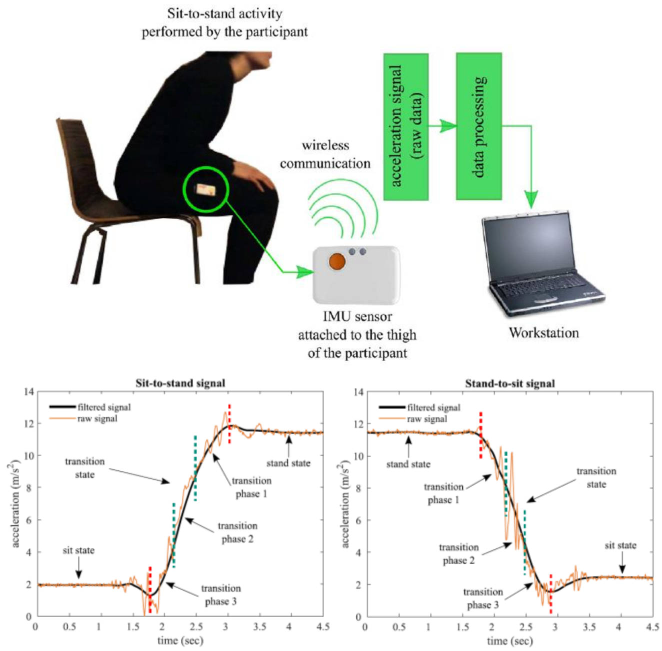

Fig. 8. (A) IMU sensors on thigh of a participant for collection of acceleration data. (B) Example data from SiSt and StSi activities.

These data were processed by a probabilistic approach for recognition of sit, transition and stand states during the SiSt activity [29]. In addition, multiple segments that compose the transition state were recognised, which is important to achieve a robust and accurate control of assistive robots. Results for recognition of SiSt states and transition segments are shown in Figure 9. Similar to the walking recognition experiment, where this process was performed in a controlled laboratory environment. Other aspects that need to be considered in a real or outdoor environment could affect the recognition accuracy of SiSt. Some of these aspects are the delays in the pre-processing steps to smooth the signal, type of chair, optimal location of sensors and speed to move from sit to stand.

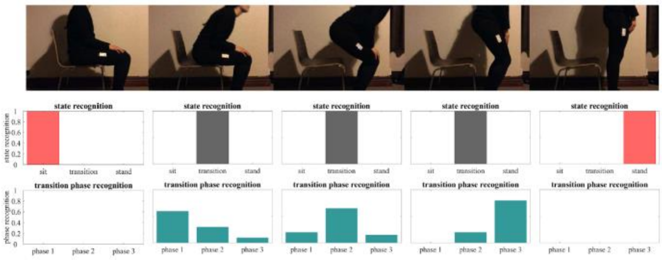

Fig. 9. Recognition of SiSt (top). Participant performing the SiSt activity with one IMU. (middle) Recognition of sit, transition and stand states. (bottom) Recognition of multiple segments during the transition state.

From these two experiments, for recognition of walking and SiSt activities, it was possible to achieve fast and highly accurate performance using kinematics information. Particularly, angular velocity and acceleration data were collected in offline mode. To achieve a similar performance in outdoor environments, there are various factors, in software and hardware that need to be taken into account. For instance, delays in recognition response due to pre-processing steps, noisy measurements, optimal location of wearable sensors on the human body, calibration of sensors over time, real-time software, context awareness, batteries, unexpected activities, etc. All these aspects make the development of wearable systems for recognition and assistance to humans in real-time and outdoor environments challenging.

4. DISCUSSION

The market of assistive gait wearable robots is expected to grow in the next few years to be used in healthcare for rehabilitation, industry for enhancing worker ability when they do heavy tasks, or to help elderly people. The gait of wearer in the wearable robots need to be assessed objectively to improve the AGWR design and control system. The objective assessment of the wearable robotics will lead to the future self-adaptable and smart devices including exoskeletons, orthoses, and prosthetics that easily adapt to the user and environment requirement. In this paper, the assessment parameters were divided into two categories: 1) parameters leading to assessment of the interaction comfort level for the user while using the device, 2) parameters that assess the overall system functionality including the user and the device together. Table I summarises these parameters and how they can be measured using motion capture systems or wearable sensors.

Considering the wearer with the AGWR, using motion capture system will be useful mainly for the parameters limited to be measured in indoor, inside the gait analysis laboratory. This cannot help the researchers to assess the wearable robots in the real outdoor environment and it cannot be used to support the control system decisions in the real-time either. Hence, there is a need to have embedded gait analysis capability within the wearable robotics. This can be implemented using smart wearable sensors to switch the assessment technology from a laboratory environment to real-world applications. According to Table I, there are still some challenges to measure some parameters using wearable sensors. For example, currently using an embedded sensory system cannot measure rollover shape, safety impact, and cognitive impacts. These challenges will need to be considered for the development of wearable sensing technology to evaluate them objectively.

5. CONCLUSIONS

In this paper, the challenges and the major parameters in designing and evaluating the AGWR for both the indoor and the outdoor environment were presented. For many decades, assistive and rehabilitation robots have been designed based on using indoor or laboratory data and in many cases only for indoor use. However, if an AGWR is needed to be utilised similar to the human limb, there are many aspects that still need to be taken into account to develop robust and safe assistive devices that work on different terrains and environment. Two major approaches for gait analysis employed in the design of assistive robots, based on vision systems and wearable sensors, were described. Exemplars of these approaches were accompanied by experiments for gait analysis with above-knee amputees and recognition of ADLs with healthy participants. Additionally, a list of essential design and performance parameters, such as comfort, safety, adaptability, compliance, and energy consumption, were presented for the development of efficient, adaptive and safe assistive robots for the outdoor environments.

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TABLE I

SUMMARY OF THE PARAMETERS AFFECT THE INTERACTION COMFORT LEVEL AND THE OVERALL SYSTEM FUNCTIONALITY

Impact		Measuring technique		
		MoCap	Wearable sensors	Others
Comfort Level	Physical impact	Inverse dynamics with MoCap	Flexi force, FSR, piezoelectric	–
	Cognitive impact	N/A	N/A	activity recognition accuracy
	Physiological impact	N/A	heart rate, EMG	VO2
	Feelings and mental efforts impact	N/A	EEG, GSR	N/A
	Safety impact	N/A	N/A	standard guideline
Device Functionality	Stability	CoP, CoM	accelerometer, IMU	–
	Energy consumption	–	can be estimated using PCI or accelerometer	VO2
	Rollover shape	CoP and kinematic analysis	N/A	–
	Static symmetry	GRF	Flexi force, FSR, piezoelectric	–
	Gait symmetry	Spatio-temporal, kinematics, and ground reaction forces	IMU and force sensors	–
	adaptability to environment	kinematics	kinematics	mechanical control system

REFERENCES

[1] C. G. Burgar, P. S. Lum, P. C. Shor, and H. M. Van der Loos, “Development of robots for rehabilitation therapy: The palo alto va/stanford experience,” Journal of rehabilitation research and development, vol. 37, no. 6, pp. 663–674, 2000.

[2] P. Allard, I. A. Stokes, and J.-P. Blanchi, Three dimensional analysis of human movement. Human Kinetics Publishers, 1995.

[3] D. H. Sutherland, “The evolution of clinical gait analysis: Part ii kinematics,” Gait & posture, vol. 16, no. 2, pp. 159 179, 2002.

[4] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola, and I. Korhonen, “Activity classification using realistic data from wearable sensors,” IEEE Transactions on information technology in biomedicine, vol. 10, no. 1, pp. 119–128, 2006.

[5] W. Tao, T. Liu, R. Zheng, and H. Feng, “Gait analysis using wearable sensors,” Sensors, vol. 12, no. 2, pp. 2255–2283, 2012.

[6] H. F. Maqbool, M. A. B. Husman, M. I. Awad, A. Abouhossein, N. Iqbal, and A. A. Dehghani-Sanij, “A real time gait event detection for lower limb prosthesis control and evaluation,” IEEE transactions on neural systems and rehabilitation engineering, vol. 25, no. 9, pp. 1500–1509, 2017.

[7] U. Martinez-Hernandez and A. A. Dehghani-Sanij, “Adaptive Bayesian inference system for recognition of walking activities and prediction of gait events using wearable sensors,” Neural Networks, vol. 102, pp. 107–119, 2018.

[8] A. Cappozzo, U. Della Croce, A. Leardini, and L. Chiari, “Human movement analysis using stereophotogrammetry: Part 1: theoretical background,” Gait & posture, vol. 21, no. 2, pp. 186–196, 2005.

[9] L. Chiari, U. Della Croce, A. Leardini, and A. Cappozzo, “Human movement analysis using stereophotogrammetry: Part 2: Instrumental errors,” Gait & posture, vol. 21, no. 2, pp. 197–211, 2005.

[10] A. T. Asbeck, S. M. De Rossi, I. Galiana, Y. Ding, and C. J. Walsh, “Stronger, smarter, softer: next-generation wearable robots,” IEEE Robotics & Automation Magazine, vol. 21, no. 4, pp. 22–33, 2014.

[11] V. Medved, Measurement of human locomotion. CRC press, 2000.

[12] M. J. Highsmith, B.W. Schulz, S. Hart-Hughes, G. A. Latlief, and S. L. Phillips, “Differences in the spatiotemporal parameters of transtibial and transfemoral amputee gait,” JPO: Journal of Prosthetics and Orthotics, vol. 22, no. 1, pp. 26–30, 2010.

[13] A. Brennan, J. Zhang, K. Deluzio, and Q. Li, “Quantification of inertial sensor-based 3d joint angle measurement accuracy using an instrumented gimbal,” Gait & posture, vol. 34, no. 3, pp. 320–323, 2011.

[14] S. C. Mukhopadhyay, “Wearable sensors for human activity monitoring: A review,” IEEE sensors journal, vol. 15, no. 3, pp. 1321–1330, 2015.

[15] R. Dumas, R. Branemark, and L. Frossard, “Gait analysis of transfemoral amputees: errors in inverse dynamics are substantial and depend on prosthetic design,” IEEE transactions on neural systems and rehabilitation engineering, vol. 25, no. 6, pp. 679–685, 2017.

[16] A. Abouhossein, B. Weisse, and S. J. Ferguson, “A multibody modelling approach to determine load sharing between passive elements of the lumbar spine,” Computer methods in biomechanics and biomedical engineering, vol. 14, no. 06, pp. 527–537, 2011.

[17] Z. W. Lui, M. I. Awad, A. Abouhossein, A. A. Dehghani-Sanij, and N. Messenger, “Virtual prototyping of a semi-active transfemoral prosthetic leg,” Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, vol. 229, no. 5, pp. 350–361, 2015.

[18] A. H. Vrieling, H. G. Van Keeken, T. Schoppen, A. L. Hof, B. Otten, J. P. Halbertsma, and K. Postema, “Gait adjustments in obstacle crossing, gait initiation and gait termination after a recent lower limb amputation,” Clinical Rehabilitation, vol. 23, no. 7, pp. 659–671, 2009.

[19] F. Gottschalk and M. Stills, “The biomechanics of trans femoral amputation,” Prosthetics and orthotics international, vol. 18, no. 1, pp. 12–17, 1994.

[20] L. Sapp and C. Little, “Functional outcomes in a lower limb amputee population,” Prosthetics and orthotics international, vol. 19, no. 2, pp. 92–96, 1995.

[21] A. Leardini, L. Chiari, U. Della Croce, and A. Cappozzo, “Human movement analysis using stereophotogrammetry: Part 3. soft tissue artifact assessment and compensation,” Gait & posture, vol. 21, no. 2, pp. 212–225, 2005.

[22] U. Della Croce, A. Leardini, L. Chiari, and A. Cappozzo, “Human movement analysis using stereophotogrammetry: Part 4: assessment of anatomical landmark misplacement and its effects on joint kinematics,” Gait & posture, vol. 21, no. 2, pp. 226–237, 2005.

[23] S. Bruijn, O. Meijer, P. Beek, and J. Van Die¨en, “Assessing the stability of human locomotion: a review of current measures,” Journal of the Royal Society Interface, vol. 10, no. 83, p. 20120999, 2013.

[24] H. Sadeghi, P. Allard, F. Prince, and H. Labelle, “Symmetry and limb dominance in able-bodied gait: a review,” Gait & posture, vol. 12, no. 1, pp. 34–45, 2000.

[25] R. Andres and S. Stimmel, “Prosthetic alignment effects on gait symmetry: a case study,” Clinical biomechanics, vol. 5, no. 2, pp. 88–96, 1990.

[26] S. Cabral, R. A. Resende, A. C. Clansey, K. J. Deluzio, W. S. Selbie, and A. P. Veloso, “A global gait asymmetry index,” Journal of applied biomechanics, vol. 32, no. 2, pp. 171–177, 2016.

[27] D. Gouwanda and S. A. Senanayake, “Identifying gait asymmetry using gyroscopesa cross-correlation and normalized symmetry index approach,” Journal of Biomechanics, vol. 44, no. 5, pp. 972–978, 2011.

[28] U. Martinez-Hernandez, I. Mahmood, and A. A. Dehghani-Sanij, “Simultaneous bayesian recognition of locomotion and gait phases with wearable sensors,” IEEE Sensors Journal, vol. 18, no. 3, pp. 1282–1290, 2017.

[29] U. Martinez-Hernandez and A. A. Dehghani-Sanij, “Probabilistic identification of sit-to-stand and stand-to-sit with a wearable sensor,” Pattern Recognition Letters, 2018.